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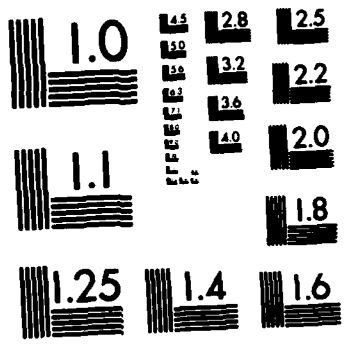

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A cognitive theory of user/expert system interaction is proposed that relates the quality of cooperative problem solving with an expert system to: (1) cognitive consistency, the degree of consistency between the rule-based system and the user's problem solving processes; and (2) mental model, the user's conceptual understanding of the basic principle of the system's problem solving processes. An experimental study is described that strongly supports the theoretical prediction. In particular, the results support the prediction that for users with an accurate mental model, increasing cognitive consistency (over)

cont

significantly decreases user/expert system problem solving performance. Users not possessing an accurate mental model reach higher performance when utilizing cognitive consistent procedures. The practical implications of this theory are briefly discussed. Originator-supplied keywords include: Human factors, and Man/machine interface.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

INTRODUCTION

Expert System technology has in recent years advanced to the point where it is being increasingly viewed as a practical tool for supporting decision makers addressing significant real world decision problems. Associated with this trend, however, has been some concern about the nature of user interaction with expert systems and understanding the conditions under which cooperative and effective user/expert system problem solving behavior can occur.

This paper describes empirical research investigating the cognitive psychology of user interactions with expert systems. This research was performed in the context of a more general research program that focuses on achieving two interrelated goals: (1) to advance a general understanding of the psychology of user interactions with intelligent machines; and (2) to generate design principles that lead to the optimal user engineering of future expert systems.

The central theory discussed below is that the nature of the cognitive interaction between a user and a rule-based expert system is driven to a significant extent by two mediating variables:

1. The degree of consistency between the rule-based system and the user's problem solving processes;

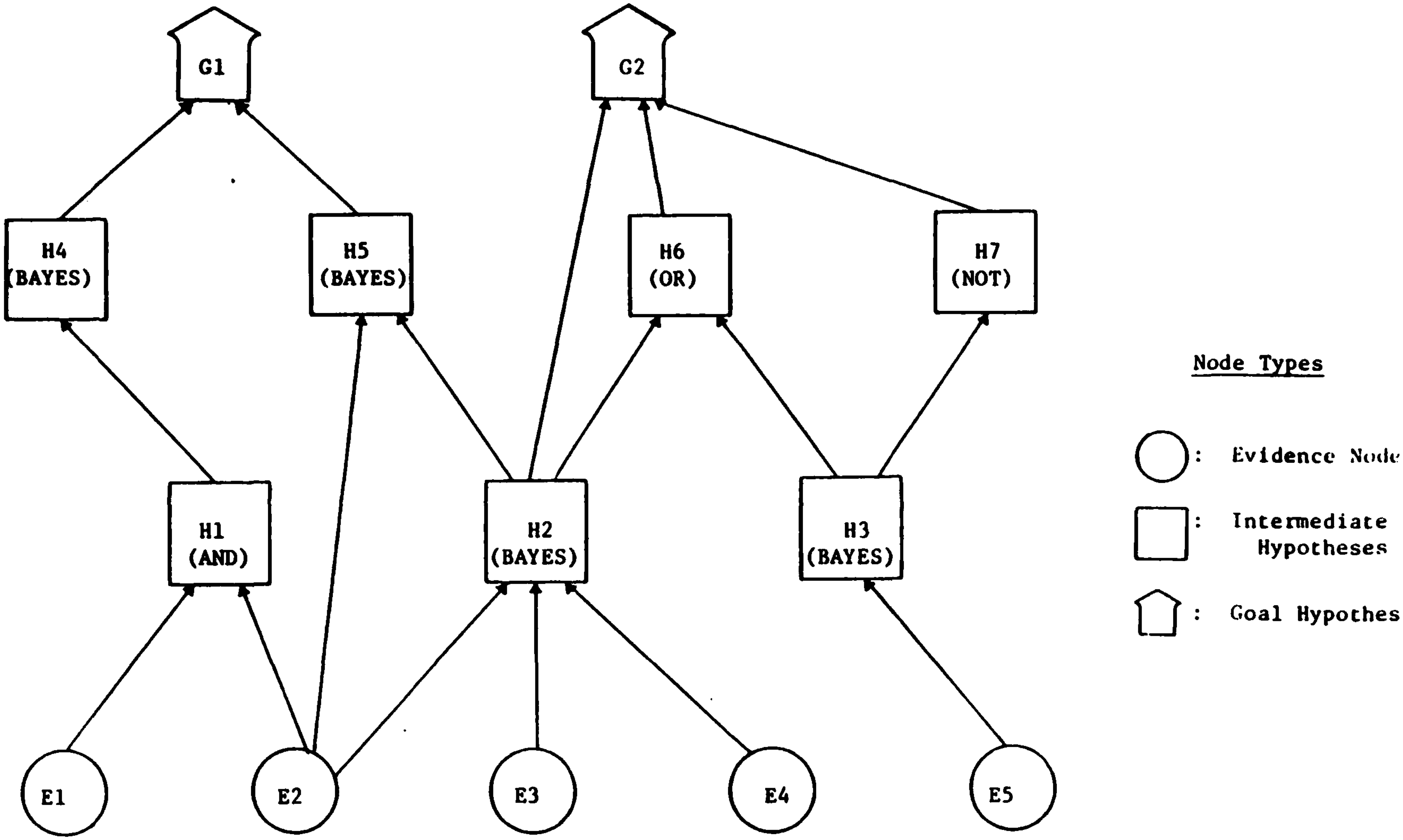
2. The user's mental model of the system's operating processes.

The remainder of this paper (1) provides a brief overview of expert system technology, (2) discusses some research relating human and expert system problem solving, (3) presents a basic theory of user interaction with an expert system, and (4) provides experimental results testing this theory.

Expert Systems in Artificial Intelligence

In the past decade, a decision aiding technology has emerged from the discipline of artificial intelligence that has the potential for greatly improving the decision speed and quality of problem solving. Expert systems are computer-based systems that provide expert advice (e.g., medical diagnoses) to users in real-world complex problem domains. Expert system design usually consists of two components: a "knowledge base" and an "inference engine". The knowledge base contains all the domain-relevant expertise. This expertise is usually encoded in the form of condition-action pairs, referred to as production rules that specify a set of heuristics about "What to do if..." The inference engine serves two functions. First, it implements general control procedures for deciding the sequence of rules to test. Second, if a mathematical model of "inference strength" is utilized, the inference engine will update the relevant values (e.g., likelihood estimates). In effect, the role of the inference engine is to apply domain specific knowledge to problem specific data to generate problem specific conclusions.

In addition to simply being encoded as production rules, a knowledge base can usually be conceptually organized into some type of nearly decomposable structure. For example, as illustrated in Figure 1, an inference network is a structure that contains top-level hypotheses, called goal hypotheses, which are decomposed into various levels of subhypotheses that are further broken down into specific items of evidence that can support those hypotheses. With each node, there is often an associated prior degree of belief



SAMPLE FORM OF AN INFERENCE NETWORK

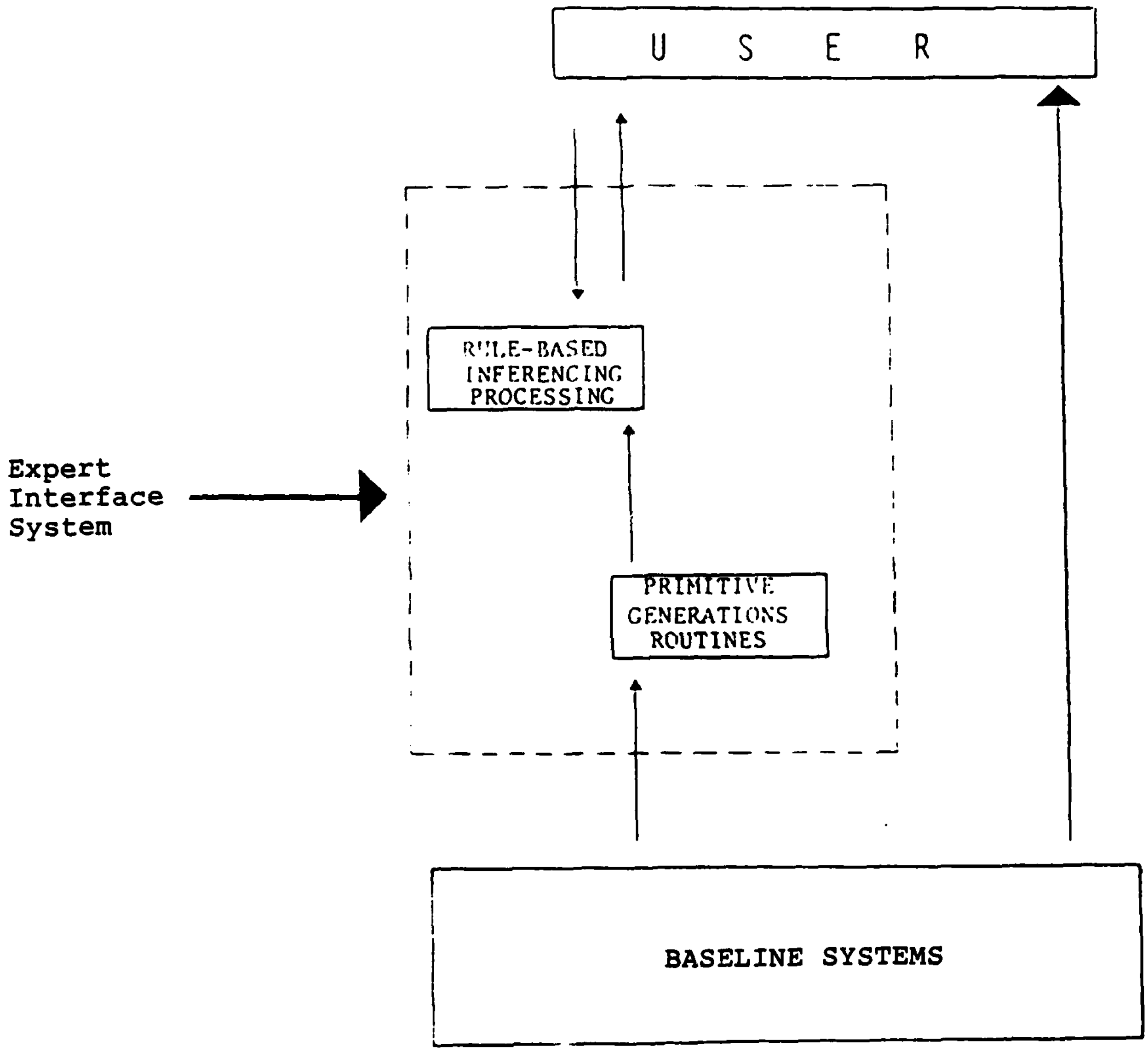
FIGURE 1

and a rule for combining subnode degree of belief values into an updated degree of belief for the node.

Most expert systems developed to date have functioned in the role of independent consultation systems, where all problem specific information required by the system is directly requested from the user. In a typical session with an expert consultation system the system attempts to evaluate the degree of belief of a goal hypothesis by chaining down the inference net, identifying the evidence items that affect the goal hypothesis, and querying the user about each relevant item of evidence. Consequently, user interactions with an expert system during a consultation session consist primarily of answering system questions and occasionally requesting an explanation of the inference process (see Duda et al., 1979; Shortliffe, 1976).

Some recent applications of expert system technology however have focused on the use of expert systems as an intelligent interface between a user and a larger complex information processing system. An <u>expert interface system</u> can be defined as a software system that uses a rule-based model to automatically monitor the contents of an external data source, generate conclusions using the data source as the primary information source, and inform the user of those conclusions along with the data that lead to the ultimate conclusions. The primary function of the expert interface system is to enhance an operator's ability to utilize an independent baseline system, but typically does not provide the sole interface to the baseline system (see Figure 2). (See Lehner, et al., 1983 for discussion.)

While expert interface systems implement the same rule-based



COMPONENTS OF EXPERT INTERFACE SYSTEMS

FIGURE 2

program architectures found in consultation systems, instead of querying the user to ascertain basic pieces of evidence, the expert interface system will call up any of a set of application specific primitive functions to evaluate evidence nodes. These primitive functions, in turn, can interrogate (get input from) external data sources (i.e., the baseline system) for factual information (see Figure 2).

From a human factors perspective, there are some key aspects of expert interface systems that make them very different from expert consultation systems. First, in a consulting system users must have sufficient domain expertise to answer the system queries, whereas expert interface systems are essentially turn key systems that obtain problem specific data from other sources. Consequently, the user community of the expert interface systems will reflect a very broad range of problem domain expertise, and such systems must be compatible with differing levels of user expertise. Second, the time constraints on the decision processes of these new interface systems is typically shorter and more diverse than was the case with consultation systems. Third, since the information inputs used by an expert interface system are obtained from an external data base, and not the user, it cannot be assumed, when a result is displayed, that the user is already intimately familiar with all the relevant data that lead to that result. A general theory of user/expert system interaction must be able to deal with both types of expert systems.

Human and Expert System Problem Solving

The processes of expressing different problem solving strategies in rule-based expert systems has lead to a consideration of human cognition in terms of similar rule-based models. Rouse (1980) describes a production system as a rank-ordered set of pattern-evoked rules of action such that actions modify the pattern, thereby evoking other actions. Human cognitive processing has been viewed in a similar way. In discussing the application of production systems to the modeling of human-computer interaction, Durrett and Stimmel (1981) conclude that production systems may provide powerful empirical and theoretical techniques for investigating human factors issues associated with interactive computer systems. Young (1979) considers the similarity between production systems and aspects of the human cognitive system as creating the potential for addressing theoretical issues in cognitive psychology.

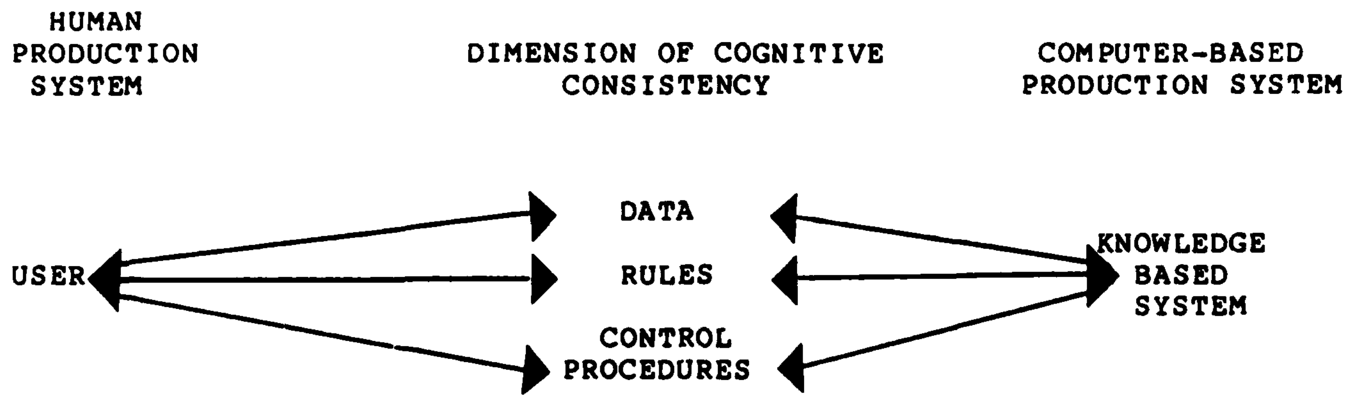
Given the above perspective on human problem solving, one way to view user interactions with expert systems is in terms of two separate production systems working in tandem to address a specific problem solving domain. Each system, both human user and expert rule base, bring some degree of domain knowledge and problem solving strategies to the decision making environment. However, it is unlikely that both system share identical data sets, problem solving heuristics (i.e., rules) or control strategies. Effective human/machine cooperative problem solving occurs when both systems' approaches combine to form one unified strategy that results in significantly higher performance than either system could have reached independently.

Basic Theory

A basic theory is proposed that relates the quality of cooperative problem solving with an expert system to: (1) cognitive consistency, the degree of consistency between the rule-based system and the user's problem solving processes; and (2) mental model, the user's conceptual understanding of the basic principle of the system's problem solving processes.

Cognitive consistency is defined as the degree to which the user and knowledge-based system utilize similar domain specific production systems. That is, the degree to which they share the same lowest level data items, product rules, and control procedures (see Figure 3).

The quality of a user's mental model is defined in terms of the user's understanding of the general principles of the system's processes, which may be formulated by both exposure to a conceptual model of the system and direct interaction with the system. In the case of expert systems, the user's mental model concerns the degree to which the user understands (1) that knowledge has been encoded as rules, (2) that rules are organized by an inference network of relationships, and (3) that explanatory traces involve chaining forward (or backward) along the inference network. Note that this definition explicitly excludes any reference to the user's understanding of the domain specific rules in the expert system, but rather focuses on a user's understanding of the basic principles of the system's processes. To the extent that the user understands the expert system's domain specific knowledge, that knowledge is incorporated into his own problem solving procedures, i.e., becomes a



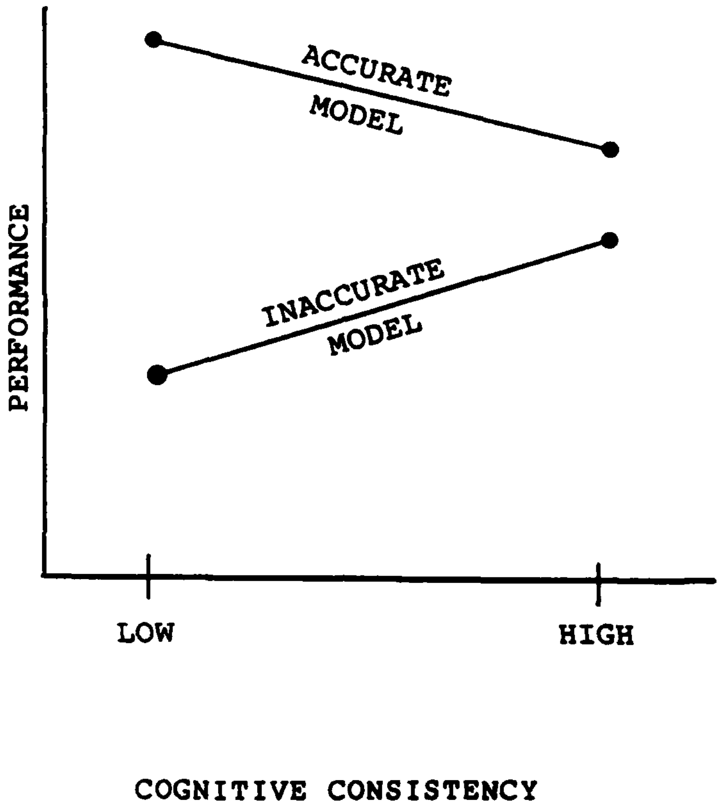
COMPONENTS OF COGNITIVE CONSISTENCY BETWEEN TWO PRODUCTION SYSTEMS

FIGURE 3

component of cognitive consistency.

The basic theory proposed here is that in a user and expert system problem solving situation, performance is dependent on both cognitive consistency and the user's mental model, and that there is a strong interaction between two variables in their impact on performance. Figure 4 shows the pattern of this predicted interaction. Obviously the strongest prediction is that a good mental model of expert system processing will facilitate user understanding of system results and explanations even if the system logic is substantially different from the user's. In particular, when a user posesses an accurate mental model, cognitive inconsistency should result in better performance than problem solving involving a high level of cognitive consistency.

Upon initial examination, this theory may appear counter-intuitive, as it predicts cognitive consistency leading to a performance decrement for users possessing accurate mental models. However, if viewed from the perspective of the user and machine as two interacting production systems then this prediction is quite reasonable. In the high cognitive consistency condition, the situation is such that the user and intelligent system are two nearly identical production systems that are solving a common problem by applying the same production rules and control strategy to the same problem specific data. Given this high degree of overlap between the two systems there is little room for cooperative problem solving to improve upon what either the user or machine could do in isolation. As cognitive consistency decreases however, the <u>potential</u> improvement of cooperative problem solving over individual user or



PREDICTION OF MENTAL MODEL/COGNITIVE CONSISTENCY INTERACTION

FIGURE 4

machine problem increases proportionately. However, in order to realize this potential, the user must still be able to effectively interact with the system. It is proposed here that an accurate mental model will facilitate user/expert system interaction, thereby permitting effective use of the system in the cognitive inconsistent condition.

Described below is an empirical test of this theory.

EXPERIMENTAL METHOD

Subjects

Thirty-two (16 male and 16 female) undergraduate students from the Catholic University of America served as volunteer subjects in this study. The mean age was 19.3 years with a range of 17-22 years. None of the subjects had previous experience with rule-based systems or computer-aided problem solving tasks.

Materials

The framework used for development of the intelligent interface was ERS, Embedded Rule Based System (Barth, 1982), which is in many respects similar to the well known PROSPECTOR system (Duda, et al., 1979). The ERS system consists of an inference engine, rule base parser, and language for representing rules. Rules in a text file are parsed and compiled into internal data structures during run-time initialization. The inference engine then uses these data structures to drive the systems decision making process. This process may involve gathering evidence from the user, as is usually done in expert consultation systems, or from a set of primitives supplied for a particular application, or both. As sufficient evidence is gathered conclusions or advice is reported in the form of the degree of belief in the top level, goal hypotheses that were defined in the rule base. The system continues gathering evidence and reporting advice, until no more evidence remains to be gathered, or the user issues a quit command. Written in Pascal, ERS was developed on a VAX-11/780 under the UNIX operating system, version 4.1 bsd. and has been installed on an IBM PC with 128K bytes of memory, under the UCSD P-System.

For this study, a simplified version of ERS was implemented on an Apple IIe microcomputer with 64K bytes of memory. The rule base representing the testbed domain consisted of an inference network containing 63 nodes, 5 goal hypotheses, 39 rules, and 109 links between nodes.

Experimental Design

A 2 x 2 factorial design was used to create the experimental conditions. The two independent variables were (1) cognitive consistency and (2) mental model (see Table 1). The two levels of cognitive consistency were created by the nature of the problem solving style used by the subject. In each problem, the expert system operates in a goal-driven, backward-chaining manner through the rule base to evaluate goals. High cognitive consistency was defined when the user is taught to problem solve in a similar goal-driven, backward-chaining manner. Low cognitive consistency occurs when the user problem solves in an almost opposite, data-driven,

TABLE 1

EXPERIMENTAL DESIGN MATRIX

Group Number	Independent Variables	
	Mental Model	Cognitive Consistency
1	Accurate	High
2	Accurate	Low
3	None	High
4	None	Low

forward-chaining process. The application of both procedures resulted in identical final solutions for all data possiblities.

The two levels of the second independent variable, mental model, were (1) accurate mental model and (2) no mental model. Subjects in the accurate mental model condition received as part of their instructions a written description of an inference network. This section described the structure of a general inference network, explained how the expert system identified goals, intermediate hypothesis, and data items, and chained up and down the network to obtain degree of certainty values for each goal. Included in this section was a pictoral display of an inference net and a simple example of its operation. By working through this section the user developed a mental model of how the expert system solved problems.

Testbed Domain

The experimental domain was a simulated stock market setting in which five different types of securities fluctuated in value during the testing sessions. The increase or decrease in security value was influenced by two types of data: (1) general market conditions, and (2) specific trading activities. Market conditions concerned the degree to which the general market state could be identified as "bear," "mixed," or "bull." Trading activities described the volumes of buying/selling during a hypothetical time frame, e.g., "Blue Chip securities were sold by 5000 shares in two weeks."

Task problems were constructed by creating patterns of specific market conditions and trading activities and defining the resultant security value fluctuations. For each possible pattern of data combinations there was exactly one of the five securities whose value increased the highest. Thus, for each task problem there was one optimum security that should be recommended for purchase.

Expert System. The expert system included an inference network in which each of the five securities was set as a goal. The experimenter provided the system with access to data concerning previous market conditions (e.g. "bear"), current market conditions (e.g., "mixed"), and the volumes and direction that each security is currently being traded. The system utilized backward-chaining procedures to validate the degree of belief in each of the lowest-level data nodes, assess value to the intermediate hypotheses, and in turn estimate the degree to which each of the five securities should be recommended for purchase. At this point the system displayed the five securities as rank-ordered (greatest to poorest) recommendations for purchase (see Figure 5) for a typical screen display of the system's results for a specific problem).

Procedure

After reading a description of the experiment and signing a consent form, subjects received the instruction booklet pertaining to their particular mental model/cognitive consistency group condition. These instructions specified the objectives, procedures, and requirements of the problem solving task. Each set of instructions previously defined the level of mental model and type of problem solving procedures to be implemented.

Subjects were seated at a large table directly in front of the expert system with ample space to arrange their individual problem solving sheets. Upon completion of the experimental booklet, subjects

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Investigated goals with degree of belief >= -100 are:

It is advisable to buy SPECULATIVE (spec)
Prior degree was 0.0. Current degree is  3.7

It is advisable to buy BONDS (bonds)
Prior degree was 0.0. Current degree is  1.8

It is advisable to buy BLUE CHIP (bluechip)
Prior degree was 0.0. Current degree is -1.8

It is advisable to buy PREFERRED (pref)
Prior degree was 0.0. Current degree is -3.7

It is advisable to buy WARRANTS (warr)
Prior degree was 0.0. Current degree is -6.0

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AN EXAMPLE OF THE SCREEN DISPLAY OF THE EXPERT SYSTEM'S RECOMMENDATIONS

FIGURE 5

received three test problems to practice use of their own procedures. The type of data presented to the subject was of the same nature, i.e., market conditions and trading activities, that the expert system utilized. Competent use of the appropriate styles of procedures, either (1) cognitive consistent or rule-driven, backward chaining, or (2) cognitive inconsistent or data-driven, forward chaining, was reached by all participants.

At this time subjects received practice interacting with the expert system. After viewing the system's prioritized list of security recommendations, users practiced querying the system for its decision rationale. In other words, the user saw what the expert system recommended for a specific problem and sought to determine "how" and/or "why" this particular recommendation was reached. Through the use of a node description command, initiatecd by the entering of a "d," carriage return, and specification of the node name to be examined, users were able to examine important components of the systems logic and reasoning. Figure 6 provides a typical screen display of a node description.

By requesting a description of this node, named "M3," the user ascertains that: (1) this node concerns the degree to which "the previous market was bull and the current market is bear"; (2) the expert systems current degree of belief in this node is 3.7; (3) there are two antecedent nodes, "cbear" of current degree of belief 3.7, and "pbull" of current degree of belief 6.0; and (4) there exists one antecedent node, "bear" of value 3.7. While this specific node description may provide little rationale itself, it does provide a window of the expert system's structure and suggests paths for further

This space concerns whether or not:

the PREVIOUS market was BULL and the CURRENT market is BEAR (m3)

TYPE: and

not asked

Prior Degree	=	0.0	
Current Degree	=	3.7	
Antecedents	cbear	0.0	3.7
	pbull	0.0	6.0
Consequents	bear	0.0	3.7

SCREEN DISPLAY OF NODE DESCRIPTION

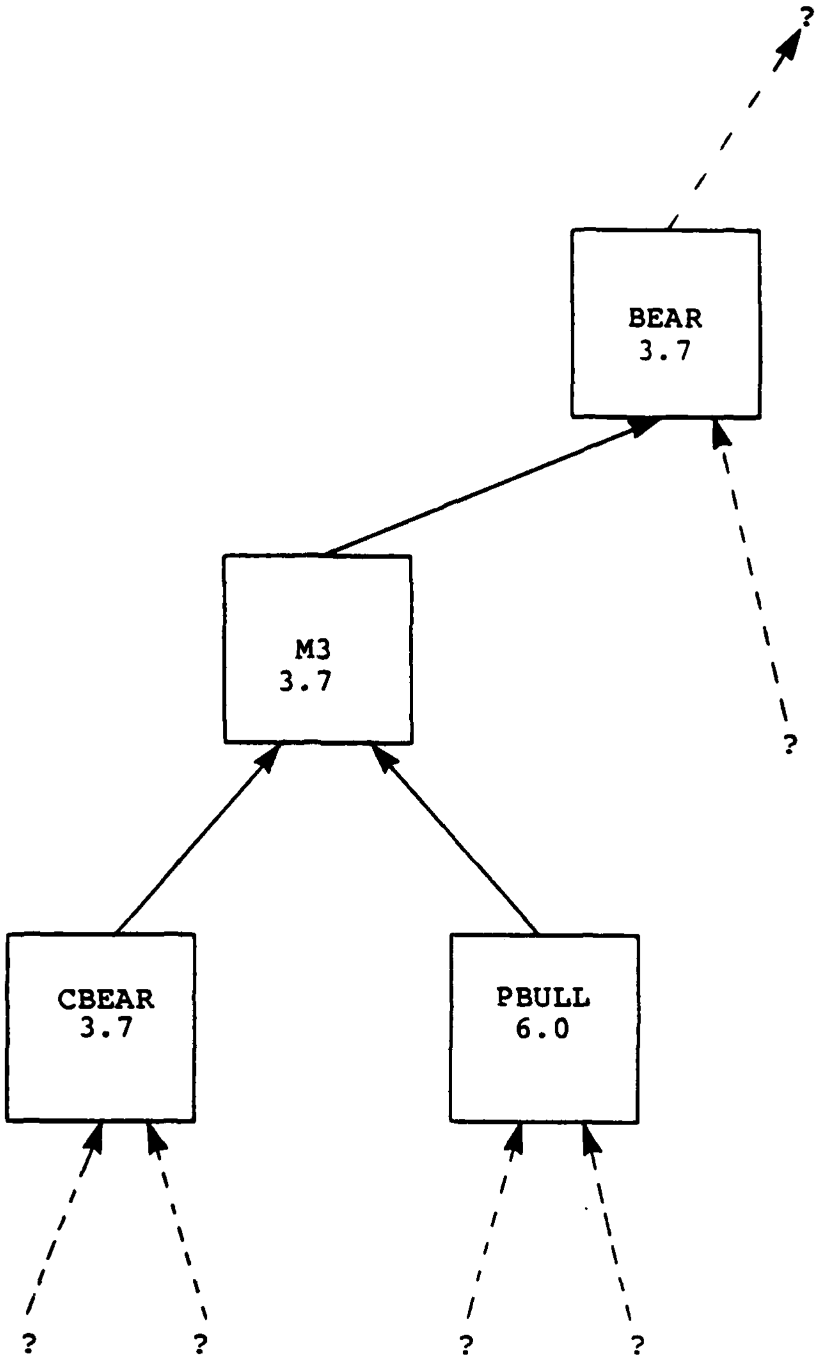
FIGURE 6

investigation, namely either "cbear" or "pbull," that may provide insight into the data the system utilized. Figure 7 provides the type of structure one may infer from the above example. Note that successful interaction with the system involves the specification of several successive node description commands to reach meaningful information, e.g., the degree of certainty of the systems lowest level data items.

The experimental process tested subjects individually for six separate problems. A time constraint of 150 seconds was imposed upon each task. Pilot studies demonstrated this time allowance as adequate for proficient interaction with the system and use of individual problem solving procedures.

Each of the problem solving tasks proceeded as follows. Seated in front of the expert interface system with individual problem solving sheets within easy reach, a subject viewed the system's rank ordered list of security recommendations for the current problem. The experimenter handed the subject written data concerning "previous market" and "current market" estimations. At this point the subject could allocate time to either querying the system with the "d" command, utilizing the individual problem solving sheets, or a combination of both. After 180 seconds, the subject viewed the system's recommendations a final time and terminated the problem solving session. The subject recorded on an answer sheet by simply checking off the one or two securities most recommended and by writing a few sentences describing why.

At the completion of six such problems, subjects completed a brief questionnaire assessing reaction to the problem solving



NODE "M3" IN THE INFERENCE NETWORK

FIGURE 7

experience and were adequately debriefed.

Performance Measures

For each of the six problem solving tasks, one of the five securities had been evaluated as the optimal recommendation during task construction. This benchmark solution was reached by utilizing problem solving procedures applied to the complete data set. It should be noted that both types of procedures, forward-chaining and backward chaining, reach the same conclusions given the same data. Thus, for each of the six problems we constructed a benchmark solution as a comparison for the subjects' responses.

The major performance measurement was the number of times a subject's response matched the predetermined optimal one. Individual scores could range from 0, none of the problems correct, to 6, all of the solutions matched with the optimal ones.

A second performance measure was the 10-item subjective questionnaire. Subjects indicated on a 10-point scale from 0 ("very strongly disagree") to 10 ("very strongly agree") their agreement with statements addressing (1) the understanding of the expert interface system's operating procedures, (2) the ease of system use, (3) the confidence of final user decisions, and (4), the adequacy of the time allotment.

Finally, the number of user queries to the expert interface system were recorded. These "d" commands were noted for each subject over each of the six problems.

RESULTS

The principle issue in this experiment was the combined effect of mental model and cognitive consistency on subjects problem solving with an expert interface system. Table 2 provides the means, standard deviations, and range for each of the four experimental groups. The data set was subjected to a 2 x 2 analysis of variance procedure investigating the main effect of each of the independent variables a well as the interaction between them (Table 3). The strong main effect of mental model, $F(1,28) = 11.15$, $p = .00214$, demonstrated that an effective understanding of the system's operating procedures facilitated cooperative problem solving quality. As predicted, a main effect for cognitive consistency did not occur, $F(1,28) = 0.0$. The presence of a significant interaction between mental model and cognitive consistency, $F(1,28) = 8.2$, $p = .0079$, confirmed our central hypothesis and theoretical basis for user/system problem solving.

A graphical presentation of subject correct responses as a percentage of total problems is depicted in Figure 8. The mental model/cognitive consistency interaction is easily observable. Individual comparisons confirmed several hypotheses. For those possessing an accurate mental model, inconsistent (forward-chaining) procedures led to a significantly greater performance, than consistent (backward-chaining) procedures $t(14) = 2.17$, $p < .05$. For users without an accurate mental model performance improved when consistent (backward-chaining) procedures were followed, although this difference failed to reach significence, $t(14) = 1.90$, $p = .079$. When evaluating the two groups implementing inconsistent procedures, subjects

TABLE 2

MEANS, STANDARD DEVIATIONS, AND RANGES FOR FOUR GROUPS

Group	Mean	SD	Range
Accurate MM/Consistent	3.375	1.4079	1-5
Accurate MM/Inconsistent	4.875	1.3562	2-6
No MM/Consistent	3.125	1.3562	1-5
No MM/Inconsistent	1.625	1.7678	0-4

TABLE 3

ANALYSIS OF VARIANCE FOR PERFORMANCE MEASURES

Source	df	SS	F	p
Mental Model	1	24.5	11.15	$<$ .01
Cognitive Consistency	1	0.0	0.0	
Interaction	1	18.0	8.2	$<$ .01
Within	28	61.5		

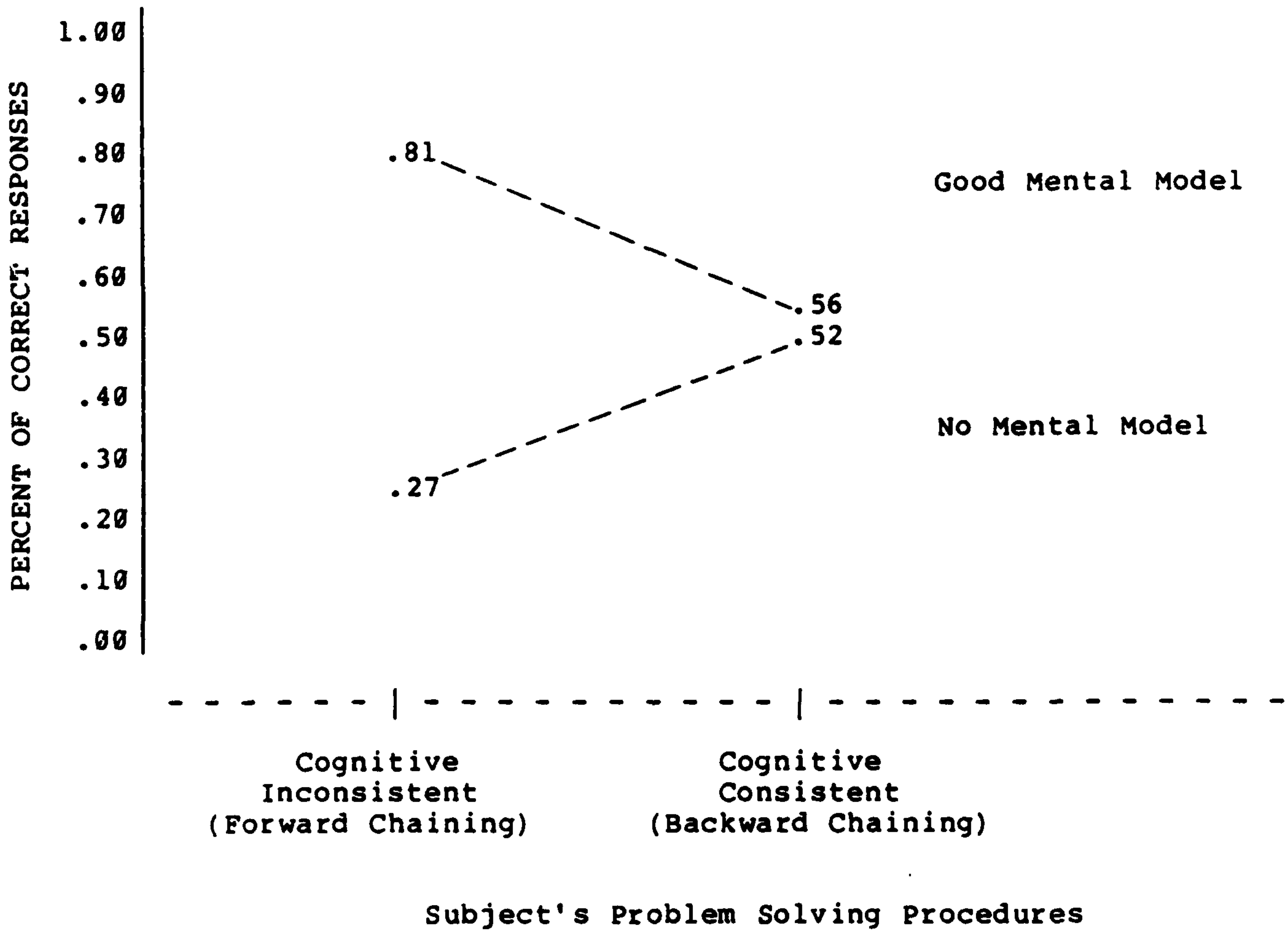


FIGURE 8

PERFORMANCE AS PERCENTAGE OF OPTIMAL RESPONSES BY GROUP possessing an accurate mental model performed significantly better, $t(14) = 4.13$, $p < .01$.

As shown in Figure 9, there was a mental model/cognitive consistency interaction predicted for each of the six test problems.

Further data analysis was performed by evaluating subjects reponses to the 10-item subjective questionnaire. Users receiving accurate mental models reported greater "understanding of the system's operating procedures," means of 5.7 and 5.7 (cognitive inconsistent and cognitive consistent respectively) than those without an accurate mental model, means of 3.4 and 3.8 respectively. Reports of "ease of system use" followed the general interaction pattern, the means being 7.9, 6.7, 6.8, and 5.8. "Confidence of final user decisions" followed the same pattern with means of 7.9, 6.7, 6.8, and 5.8. The "adequacy of the time allotment" revealed the lowest performing group of no mental model/cognitive inconsistent to be most time pressured, mean of 2.8, compared to the other three groups with means of 4.8, 5.5, and 4.4 respectively.

The final performance measure of the number of user queries during user/system interaction revealed no differences across the four conditions, the means being 5.4, 5.0, 5.3, and 5.4 respectively.

Problem 1

Mental Model	Cognitive Consistency: Low	High
Accurate	1.00	.875
None	6.25	1.00

Problem 2

Mental Model	Cognitive Consistency: Low	High
Accurate	.625	.500
None	.000	.375

Problem 3

Mental Model	Cognitive Consistency: Low	High
Accurate	.750	.500
None	.250	.375

Problem 4

Mental Model		
Accurate	.875	.375
None	.250	.250

Problem 5

Mental Model		
Accurate	.750	.500
None	.375	.375

Problem 6

Mental Model		
Accurate	.875	.625
None	.250	.750

PERCENTAGE OF CORRECT RESPONSES OF GROUP BY TASK PROBLEM

FIGURE 9

DISCUSSION AND CONCLUSION

Overall, the results of this study support the basic theory that the quality of user/expert system cooperative problem solving performance is driven to a significant extent by both the degree of consistency between the user's and expert system's problem solving procedures and the user's mental model of the expert system's problem solving processes. Highest problem solving performance was reached by users possessing a good mental model and utilizing forward-chaining (cognitive inconsistent) procedures. Our basic explanation for this result is that a user with an accurate mental model is in a position to effectively interact with the expert system despite significant differences between user's and expert system's problem solving procedures. Consequently, such a user is in a position to exploit the fact that the user and expert system have differing capabilities and areas of expertise. A user that both has inconsistent problem solving procedures and lacks an accurate mental model is not in a position to understand the expert system's procedures. Poor performance is due, in this case, to an inability to successful, interact with the expert system. Our results, therefore, indicate that problem solving requires the user to be proficient in both (1) interacting with the expert system and (2) utilizing successful individual problem solving procedures.

The questionnaire analysis was useful in several respects. First, the groups in the "accurate" mental model conditions subjectively reported greater understanding of the system's processes as would be expected. Second, reported confidence of final user decisions followed the same interaction pattern indicating that high performance and user confidence went hand-in-hand.

There were no significant differences in the actual number of user queries to the expert system during the task sessions. An explanation for this may be that users possessing an accurate mental model did not increase the quantity of node description commands, rather, they simply requested information that would be of ultimate use to them. These requests may have focused on high-quality queries, as opposed to users who did not understand the expert system's structure and obtained often irrelevant information to the immediate task at hand.

From the perspective of the potential practical implications of this theory, the most immediate impact is what the theory suggests about how user interactions with expert consultation and expert interface systems will differ. Users of expert interface systems are likely to be significantly inconsistent from the expert system in both the problem specific data they are initially aware of and the domain specific heurisitcs utilized in problem solving. Consequently, user/expert interface system interaction is a situation that naturally relfects a great deal of cognitive inconsistency. As a result, creating an accurate mendal model may be an essential ingredient for the successful transfer of interface system to operational use.

Finally, regarding the completeness of the above research as a test of the theory, it should be recognized that this initial research has operationalized cognitive consistency as the match between the user's and the expert system's procedures. While we expect the same pattern of performance to result, other dimensions of cognitive consistency need to be examined. Furthermore, a node description command was the only type of explananation a user could receive in this study. This was chosen primarily because of the imposed time constraint and the nature of the task setting. Other explanation capabilities should be examined, including a rule-trace or presentation of the system's intermediate hypotheses. Finally, user groups of diverse expertise levels should be studied over several domains and under a varying range of time constraints.

Ongoing research is currently addressing further issues in the user/system interface in an attempt toward developing a more complete set of empirically-tested theoretical principles of user/expert system interaction.

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